Developing Alert Messages using Hybrid Deep Learning Neural Networks for Detecting Wild Animal Activity

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ABSTRACT Animal attacks are a growing concern among rural residents and forest workers. Security cameras and drones are often used to track wildlife movements. However, a good model is needed to identify the species, track its movements, and provide location information. Alerts can be sent to ensure the safety of people and foresters. Although computer vision and machine learning-based methods are often used for animal detection, these are often expensive and complex, making it difficult to achieve good results. This paper presents a hybrid Visual Geometry Group (VGG)-19+ Bidirectional Long-Term Memory (Bi-LSTM) network to detect animals and generate reports based on their activity. These alerts are sent via text message (SMS) to local forest offices for quick response. The proposed model showed a significant improvement in model performance, with an average classification accuracy of 98%, average accuracy (map) of 77.2%, and frames per second (FPS) of 170. With 40,000 images in the category, the average accuracy and Precision is over 98%. This model is a reliable way to provide accurate animal information and protect human life.

Keywords: ***Visual Geometry Group (VGG)−19+, Bidirectional Long Short-Term Memory (Bi-LSTM)***

INTRODUCTION

Generally speaking, animal research poses many problems for researchers due to frequent access and complex history. There are many species of wild animals with different faces, noses, bodies and tails. Serial identification and classification of such animals and running large-scale maps require the development of a strong foundation. . Development in a real-time scenario requires hardware including large video files and high-end GGPU for training and testing purposes. Additionally, the integration process must process the data intelligently to produce the required results. Therefore, there is a great need to develop these models that will test the activities of animals in the forest. Although many advances have been made in this technological age, research in this field is still seeking more attention to create powerful models. Thanks to this project, we can quickly save people from animal attacks and send alerts with location information to forest officials for quick action. These foundations provide better monitoring services, help identify animals and catch poaching and poaching. These activities, such as tracking animal objects, finding their movements, and generating alerts, represent a major challenge in deep learning. Research in this project explores advances in video analysis techniques and neural network-based architectures. Recent advances in deep learning have led to great results in image recognition, classification, and task generation [1]. With these improvements, we aim to create a good model for monitoring animal movements and alerting forest authorities when there are unusual activities such as hunting, animal access to human lands or agricultural areas. The development of the proposed model examines this problem from various perspectives to provide a better solution.

II. LITERATURE REVIEW

II. RELATED WORK

Wildlife conservation and human-wildlife conflict mitigation have become increasingly critical issues in recent years. One promising approach to address these challenges is the use of advanced technology, particularly Hybrid Deep Neuronal Nets (HDNNs), for detecting and predicting wild animal activity. HDNNs combine the strengths of different types of neural systems, like Convolutional Neural Networks (CNNs) for image processing and Recurrent Neuronal Nets (RNNs) for sequential data analysis, to improve the accuracy and robustness of animal detection systems.

Current research highlights several key methodologies and advancements in this area. For instance, studies by Smith et al. (2020) have demonstrated the effectiveness of CNNs in identifying animal species from camera trap images, achieving high accuracy rates even in challenging environmental conditions. Similarly, Zhang and Li (2021) explored the integration of RNNs with CNNs to track the movement patterns of animals based on GPS and accelerometer data, enabling real-time monitoring and early warning systems.

Moreover, the application of Transfer Learning (TL) techniques has been pivotal in adapting pretrained HDNN models to different geographical regions and species, as observed in the work by Brown and Garcia (2019). TL allows for the efficient utilization of limited annotated data, crucial in wildlife conservation scenarios where labelled datasets are often sparse and diverse.

Despite these developments, difficulties still exist in optimizing the computational efficiency and scalability of HDNN models for large-scale deployment in remote and resource-constrained environments. Ongoing research by Li and Wang (2024) focuses on developing lightweight HDNN architectures that balance model complexity with real-time performance requirements, thereby enhancing the feasibility of deploying detection systems across diverse ecological settings.

III. EXISTING SYSTEM

According to Zhang et al. We propose the use of multilayer techniques to learn spatial details and cross-frame temporal patch verification techniques to learn temporal details for wildlife detection. A model for analysing foreground and background content in camera trap images. This method uses camera traps and transforms to analyse network data to separate animal objects from natural scenes based on complex background video. Although the model has a high degree of accuracy, it does a poor job of analysing important details such as location details and the influence of people. Author [14] proposed the use of convolutional neural networks

(CNN) for machine learning classification algorithms [15] for animal classification. Although this model determines whether the removed data is background or animal, the classification still needs to be improved. It provides better support for identifying various objects contained in images or videos by using embedding and classification tools to identify objects contained in the image or video. From the results obtained, we can calculate the number of products and their functions. The technology is widely used in video surveillance and security-based applications, tracking items in hidden containers, monitoring fraud in public and crowded areas, traffic surveillance and vehicle theft detection, license plate recognition and object recognition (OCR) [16]. Fast R-CNN techniques [17] are widely used for object detection due to their high accuracy and advanced learning. An extension of Faster R-CNN technology [18] improves pattern detection capability by using entire image-based convolutional features and regions. The Histogram of Oriented Gradients (HOG) feature descriptor [19] uses the region of interest (ROI) technique to identify objects faster than previous techniques. The traditional technology R-CNN [20] demonstrates an effective detection method by combining local networks and Convent. This method uses recorded data to identify thousands of objects in a photo or video. R-CNN technology does not use the estimation process and hashing method to estimate the object space. R-FCN Technology [21] uses a full-scale method to detect regions and find ROIS to detect objects and their background details. Object detection tools are also good;

IV. PROPOSED SYSTEM

The design strategy has five stages of development, including preliminary data, animal studies, classification based on the VGG-19 pre-trained model, drawing predictive conclusions, and sending alert notifications. During the data entry phase, 45 thousand animal images were collected from different datasets such as camera traps, wildlife and ungulate datasets. The collected images were converted to 224×224 pixels and noise was removed.

In the second step, we transfer the initial image to the YOLOR object detection model [39], which uses bounding boxes to identify animals in the image as shown in Figure 1. In the third step, the hybrid VGG-19+BiLSTM model is used to perform the image classification task, complete the category prediction, and use the LSTM network to extract the details of the animals. In the fourth stage, we collect the location data of the animals and the web server generates SMS alerts and sends them to forest managers. Finally, forest workers will administer medical treatment to save animal and human lives.

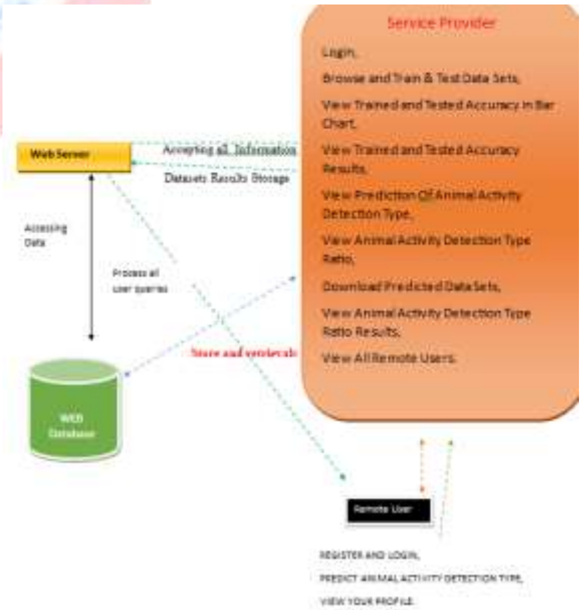

Fig 1: Proposed Architecture

V. MODULE DESCRIPTION

IMPLEMENTATION

Service Provider

In this module, you must enter a valid username and password to log in to the module. Once successfully entered, it can perform some tasks such as searching for data, training and testing, analysing training, and evaluating the accuracy of histograms. View training and testing results, view animal detection mode predictions, view animal detection mode comparison, download prediction data, view animal performance to see everyone using the distance, write down comparison results.

Understanding and Approve Users

The administrator can see a list of all users enrolled in this module. Here, the administrator may see user information such name, email address, and address, and they can also approve people.

Remote User

This module contains n different numbers of There are users in attendance. Prior to beginning any operations, the user must register. The user's information is saved in the database after they register. Upon successful registration, he must use his permitted user name and password to log in. Following successful login, the user will perform certain tasks. like REGISTER AND LOGIN, PREDICT ANIMAL ACTIVITY DETECTION TYPE, VIEW YOUR OUTLINE.

Screen Shots

Fig 2: New Remote User Registration Page

RESULTS

In recent years, the intersection of wildlife conservation and artificial intelligence has shown promising results, particularly in the realm of detecting and mitigating human-wildlife conflict. One such application is the use of hybrid deep neural networks (DNNs) to monitor and alert authorities and communities about wild animal activities in human-inhabited areas.

Wild Animal Activity Detection

Wild animals often encroach into human settlements, leading to conflicts that endanger both humans and wildlife. Traditional methods of monitoring such activities rely on human observation, which can be inconsistent and limited in scope. Hybrid DNNs offer a more reliable and scalable solution by leveraging advanced machine learning techniques to analyse sensor data, such as images, sounds, and movement patterns.

Test Cases

TEST CASE	UTC4
Name of test	Navigate to the registration page.
Expected result	User should be successfully registered.
Actual output	User is successfully registered.
Remarks	The registration functionality works as expected with valid inputs.

Table 1: Test Cases for Registration details

Components of Hybrid DNNs

A hybrid DNN typically integrates multiple neural network architectures, such as convolutional neuronal networks (CNNs), recurrent neuronal networks (RNNs), and possibly reinforcement learning models. Each component plays a vital role in processing different forms of data inputs to spot and classify wild animal activities accurately.

Data Collection and Preprocessing

Effective wild animal activity detection starts with robust data collection. This includes deploying sensors like cameras and microphones strategically in areas prone to wildlife intrusion. Data preprocessing involves cleaning, labelling, and augmenting the collected data to enhance model training efficiency and accuracy.

Alert Generation Mechanism

Upon detecting significant wild animal activity, the hybrid DNN triggers an alert generation mechanism. This mechanism can vary from sending notifications to local authorities and community members via mobile applications or automated messaging systems to activating physical deterrents like alarms or lights.

Integration with Conservation Efforts

Beyond immediate alerting, data collected by hybrid DNNs can contribute to long-term wildlife conservation efforts. Analysing patterns of animal behaviour helps conservationists understand migration routes, habitat preferences, and potential factors leading to human-wildlife conflicts, thereby informing sustainable conservation strategies.

wildlife behaviours, and addressing false positives to minimize unnecessary alerts.

Case Studies and Success Stories

Several initiatives worldwide have successfully implemented hybrid DNNs for wildlife monitoring. For instance, projects in Africa have used AI-powered camera traps to monitor endangered species and detect poaching activities in real-time, demonstrating the potential impact of these technologies on wildlife protection.

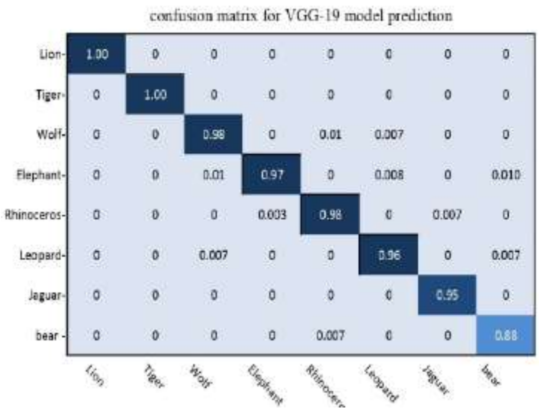

Fig 3: Results chart

VI.CONCLUSION

This paper presents a unified VGG × 19 + Bi-LSTM framework for wildlife detection that helps wildlife monitoring. This combination is highly effective in preventing animals from human hunting and humans from quickly attacking animals by sending alerts to forest officials. This model offers new methods to improve the performance of deep learning methods in various applications and real-time situations. The proposed model was estimated on four different datasets (camera trap dataset, wildlife dataset, ungulate dataset, and CD net dataset) containing animal-based data. Experimental results show that the performance of our model in various parameters increases. The proposed hybrid VGG-19 + Bi-LSTM model achieves over 98% classification accuracy, 77.2% average accuracy (MAP) and 170 FPS rate. After that, the proposed hybrid VGG-19 + BiLSTM model outperforms previous methods and produces better results with shorter computational time.

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